

Implementation of Machine Learning Classification Algorithm Based on Ensemble Learning for Detection of Vegetable Crops Disease

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Abstract—In India, plant diseases pose a significant threat to food security, requiring precise detection and management protocols to minimize potential damage. Research introduces an innovative ensemble machine learning model for precise disease detection in tomato, potato, and bell pepper crops. Utilizing transfer learning, pre-trained models such as MobileNet and Inception are fine-tuned on a dataset of over 10,403 images of diseased and healthy plant leaves. The models are combined into a diverse ensemble, enhancing the precision and robustness of disease detection. The proposed ensemble models achieve an impressive accuracy rate of 98.95%, demonstrating their superiority over individual models in reducing misclassification and false positives. This advancement in plant disease detection provides valuable support to farmers and agricultural experts by enabling early disease identification and intervention.

Keywords—DNN; transfer learning; crop; ensemble model; deep stacking and stacking approach; image pre-processing; tomato; bell pepper; potato; disease

I. INTRODUCTION

In recent years, machine learning techniques have demonstrated significant potential in the field of plant disease detection [1]. This study introduces an innovative ensemble model that surpasses traditional approaches. This novel ensemble model combines several pre-trained models, including MobileNet, Inception, and ResNet, using a comprehensive dataset [2]. The primary objective of the model is to enhance the accuracy and resilience of conventional disease detection methods. This paper offers a thorough examination of the proposed model, elucidating its intricacies, and presents experimental results demonstrating its effectiveness in detecting plant diseases in tomato, bell pepper, and potato crops. In India, tomato, potato, and bell pepper are vital crops that make substantial contributions to the country's agricultural economy. However, these crops are vulnerable to various diseases that pose a significant threat to their yield. Notable tomato diseases in India include Spider mites, specifically the Two-spotted spider mite, Tomato mosaic virus, Target spot, Septoria leaf spot, Tomato Yellow Leaf Curl Virus, Late blight, Leaf Mold, Early blight, and Bacterial spot [3]. In contrast, potato crops are susceptible to fungal diseases like Early blight and Late blight, while bell pepper crops face the threat of bacterial spot disease. These collective diseases lead to substantial decreases in crop yield and quality, resulting

in economic hardships for farmers [4]. The Deep Stacking ensemble technique, as depicted in Fig. 1, involves training a set of base models and using their predictions as input for a higher-level advanced model. This advanced model, positioned at a higher level, is trained to merge the predictions derived from the base models, resulting in a final prediction. This approach has demonstrated its ability to enhance the accuracy and resilience of models. Nevertheless, the proposed ensemble model surpasses both of these methodologies in terms of accuracy.

Plant diseases pose a significant menace to global agricultural output and food security. The precise and early detection of plant diseases is of paramount importance for effective disease management and the mitigation of crop losses. This research paper introduces a comprehensive methodology for detecting diseases in three pivotal plant species: potato, tomato, and bell pepper. These crops play vital roles in global food production but are susceptible to a wide range of diseases that can significantly impact yield and quality. The proposed model leverages ensemble learning, deep stacking, and transfer learning, employing well-established convolutional neural network architectures, including MobileNet_v2, ResNet_v2, and Inception_v3 models. Ensemble learning enables the combination of multiple models, harnessing their diverse capabilities to enhance overall detection accuracy and robustness [5]. Deep stacking allows the capture of intricate interactions among the predictions of different models, thereby improving disease classification performance. Transfer learning plays a crucial role in the methodology. By leveraging pre-trained models trained on extensive image datasets like ImageNet, Proposed model can utilize their learned features and representations, which are transferable to various visual recognition tasks. Fine-tuning these models on plant disease dataset enables us to adapt their knowledge specifically to the challenges of disease detection in potato, tomato, and bell pepper plants. The objective of the model is to develop an automated and accurate disease detection system tailored to these specific plant species by harnessing the power of machine learning techniques, particularly ensemble learning and deep stacking. The significance of this work lies in its potential to elevate disease management practices within agriculture. By enabling early disease detection, farmers and agricultural experts can swiftly implement precise treatments and crop protection strategies,

thereby minimizing the adverse effects of diseases on both crop yield and quality.

Within this research paper, an elaborate exposition of the employed methodology is provided, encompassing the application of ensemble learning and deep stacking techniques using transfer learning models like MobileNet_v2, ResNet_v2, and Inception_v3. The assessment of performance is discussed, exploring practical implications of the proposed model's disease detection system in real-world agricultural contexts, and shedding light on prospective avenues for future research to enhance the system. Ultimately, this research aims to contribute to the advancement of automated disease detection systems in agriculture, with a specific focus on potato, tomato, and bell pepper plants. By harnessing the power of ensemble learning, deep stacking, and transfer learning, the aim is to improve disease management practices, increase crop productivity, and ensure food security in the face of plant diseases.

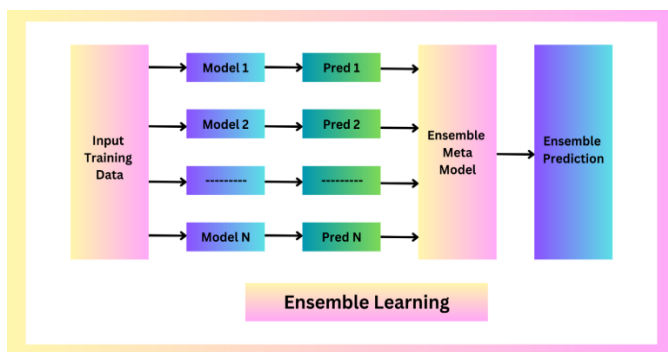


Fig. 1. Block diagram of ensemble learning model.

II. RELATED WORK

First, Tulshan et al. [1], the authors presented a study on the detection of various plant leaf diseases. They focused on detecting diseases such as Early Blight, Mosaic Virus, Down Mildew, White Fly, and Leaf Miner. The authors achieved a high accuracy of 98.56% with their proposed K-Nearest Neighbors (KNN) model. This model was trained on a dataset consisting of 75 images. Furthermore, they compared the performance of their KNN model with a basic Support Vector Machine (SVM) model, which was trained on a larger dataset of 150 images. The SVM model achieved an accuracy of 97.6%. This research highlights the effectiveness of the KNN model in accurately detecting plant leaf diseases with a relatively smaller training dataset, outperforming the SVM model trained on a larger dataset. Ramesh et al. [6], the authors addressed the issue of detecting and classifying Rice Blast disease. Their approach utilized an Artificial Neural Network (ANN) algorithm. The training phase of their model achieved an accuracy of 99%, while the testing phase yielded a respectable accuracy of 90%. The authors gathered a dataset consisting of 300 images. These images were subjected to preprocessing steps, which involved conversion to the HSV color space and subsequent K-means clustering. It's worth noting that the dataset used in this research was their own, emphasizing the unique contribution of their work in the context of Rice Blast disease detection and classification. Lee et al. [7], conducted research on disease detection in potato

leaves, specifically targeting Potato Early Blight and Late Blight. They employed Convolutional Neural Networks (CNN) as their chosen algorithm, achieving an impressive accuracy rate of 99.09% in their experiments. The authors collected and utilized a dataset comprising 2150 images for their research. Furthermore, they conducted a comparative analysis by evaluating CNN against other machine learning algorithms such as Artificial Neural Networks (ANN), Backpropagation Neural Networks (BPNN), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), among others. The results, presented in a table, demonstrated that the CNN model outperformed all other algorithms, yielding the highest accuracy of 99.09%. This survey provides valuable insights into the effectiveness of CNN in the detection of Potato Early Blight and Late Blight diseases in potato leaves, showcasing its superiority over various alternative methods. Asif et al. [8], the authors explored various Convolutional Neural Network (CNN) architectures, including AlexNet, VggNet, ResNet, LeNet, and a Sequential model, for the detection of diseases on potato leaves. The specific diseases targeted were early blight, late blight, and Septoria blight. Their research achieved an accuracy rate of 97.00% in disease detection. To support this, they used a dataset containing 3000 images and employed a basic CNN approach, which involved image processing techniques and data augmentation to enhance training. It's worth noting that the training process for this model was conducted manually, underscoring the meticulous effort and expertise invested in the research. This study provides valuable insights into the application of various CNN architectures for effective disease detection on potato leaves, showcasing a high level of accuracy in identifying these plant diseases. Tembhrne et al. [9], the authors conducted research on the detection of plant diseases, specifically focusing on early blight and late blight. Their study utilized two deep learning models, namely AlexNet and GoogLeNet, as image classifiers. They evaluated the performance of these models on five key parameters: Accuracy, Precision, Sensitivity, F1 score, and Specificity. To support their research, the authors employed a dataset containing 900 images. The experimental outcomes showcased a remarkable 98.52% accuracy in identifying various plant diseases. Notably, the research was carried out on Kaggle, a widely recognized platform for data science and machine learning competitions and collaborative projects. This investigation offers valuable perspectives on the efficacy of deep learning models such as AlexNet and GoogLeNet in the realm of plant disease detection, highlighting their high accuracy and the use of comprehensive evaluation metrics. Naveen kumar et al. [10], the authors focused on the classification of plant diseases, specifically targeting early blight and late blight. For their research, they employed the InceptionResNetV2 model, achieving a commendable accuracy rate of 95.30%. To support their findings, the authors conducted a comparative analysis with other deep learning architectures, including VGG (16 and 19), ResNet 50, and InceptionV3. Interestingly, their results revealed that InceptionResNetV2 outperformed these models, showcasing a superior accuracy rate of 95.3%. It's worth noting that the dataset used in this research was proprietary, emphasizing the unique contribution of their study in the field of plant leaf disease classification. This research underscores the

effectiveness of InceptionResNetV2 as a robust model for accurate and reliable plant disease classification. Kukreja et al. [11], the authors addressed the challenge of potato disease classification, specifically focusing on Potato Early Blight and Late Blight, their approach employed a simple CNN based deep learning model. Through their research, they achieved a notable accuracy rate of 94.77%. The authors not only discussed basic classification results but also provided insights into classification metrics such as F1 score and recall. This study was conducted using a dataset consisting of 900 images and were part of the Plant Village project, emphasizing its contribution to the broader field of plant disease classification. The research highlights the effectiveness of their CNN-based model in accurately classifying potato diseases, particularly Early Blight and Late Blight. Tiwari et al. [12], the authors tackled the challenge of detecting potato leaf diseases, specifically focusing on Potato Early Blight and Late Blight. Their research introduced a novel approach by proposing a VGG19-based model. This model utilized VGG19 as a feature extractor, building upon the CNN architecture. In their experiments, the authors compared the performance of their VGG19-based model with VGG16 and Inception models. The dataset used for their study consisted of 2152 images, and their approach yielded an impressive accuracy rate of 97.80%. This research was conducted as part of the Plant Village project, emphasizing its contribution to the field of plant disease detection. The study underscores the effectiveness of their VGG19-based model in accurately detecting Potato Early Blight and Late Blight in potato leaves. Sinshaw et al. [13], the authors addressed the task of detecting Potato Late Blight disease. They employed three pre-trained CNN models, namely VGG16, VGG19, and InceptionV3, to explore the potential of transfer learning and data augmentation in disease detection. The results of their experiments demonstrated varying levels of accuracy among the three models. InceptionV3 emerged as the top-performing model, achieving an accuracy rate of 94.11%. In comparison, VGG16 achieved an accuracy of 93.2%, and VGG19 achieved 92.9%. These findings indicated that InceptionV3 outperformed VGG16 and VGG19 in detecting Potato Late Blight disease. The authors conducted their research using a dataset comprising 430 images, and it's noteworthy that the dataset was developed in-house, emphasizing the unique contribution of their study. This research highlights the effectiveness of transfer learning and data augmentation techniques, particularly when applied to the InceptionV3 model, in accurately detecting Potato Late Blight disease. Lakshmanarao et al. [14], the authors focused on predicting and classifying plant diseases, particularly within 15 classes encompassing Tomato, Pepper, and Potato. Their research employed ConvNets as the primary methodology. The study produced impressive accuracy rates for disease prediction and classification, with a notable 95% accuracy for Tomato, 98.5% for Bell Pepper, and 98.3% for Potato. To support their findings, the authors worked with a substantial dataset comprising 20,638 images. This research was conducted as part of the Plant Village project, underlining its valuable contribution to the field of plant disease prediction and classification. The study emphasizes the effectiveness of ConvNets in achieving accurate disease identification within the Tomato, Pepper, and Potato plant categories. Karthik et al.

[15], the authors focused on predicting diseases in Tomato and Potato plants and their potential health benefits. Their research utilized a basic CNN approach, involving feature extraction and CNN model generation. This approach yielded a high accuracy rate of 98% in disease prediction for Tomato and Potato plants. The study was conducted as part of the Plant Village project, emphasizing its contribution to the field of plant disease prediction and its potential impact on the health benefits associated with these plants. The research underscores the effectiveness of their CNN-based deep learning techniques in accurately predicting diseases in Tomato and Potato plants.

Crop sustainability and food security pose pressing challenges in agricultural development. The early detection of plant diseases holds paramount importance in addressing these challenges. This study focuses on three crucial plant species: potato, tomato, and bell pepper, which are integral components of the global diet. It addresses the detection of seven different types of diseases. Plant diseases have garnered increasing attention in recent years, posing a significant threat to food security in India and around the world. Detecting these diseases demands expertise, time, and substantial human effort, as it requires proficiency in disease identification. Early disease detection is critical for minimizing damage and increasing crop yields, with far-reaching implications for the global economy. To tackle this issue, a novel ensemble model for plant disease detection is proposed in this research. This model leverages the capabilities of MobileNet, Inception, and ResNet models, which have been pre-trained on extensive image datasets, making them ideal for feature extraction in the proposed framework.

In this research, ensemble learning technique for vegetable leaves disease detection is implemented in the Google Colab environment, which utilizes GPU and TPU. The dataset comprises 10,403 images collected from primary sources and PlantVillage. Diverse image pre-processing methods, encompassing techniques like augmentation, Canny edge detection, noise reduction, and others, are utilized to extract distinctive features from images of plant leaves. Furthermore, implement transfer learning algorithm and then design Ensemble learning Algorithm. Their performance on various evaluation metrics, such as accuracy, f1-score, recall, and precision, is compared. These results are then compared with those obtained from the proposed ensemble model.

While the studies discussed have made significant contributions to plant disease detection, they also exhibit certain limitations that make them less suitable for our problem. For instance, the models proposed by Tulshan et al. [1], Ramesh et al. [6], and Lee et al. [7] were trained on relatively small datasets, which may limit their generalize ability to larger, more diverse datasets. The models used by Asif et al. [8] and Sinshaw et al. [13] demonstrated varying levels of accuracy, indicating a lack of consistency in their performance. Furthermore, the models employed by Naveenkumar et al. [10] and Kukreja et al. [11] were trained on proprietary datasets, which may limit the reproducibility of their results. Our proposed ensemble machine learning model addresses these limitations by leveraging the strengths of multiple pre-trained models and fine-tuning them on our extensive dataset. This approach enhances the precision and

robustness of disease detection, making it more suitable for the problem at hand.

III. PROPOSED MODEL

The proposed model for this research is an ensemble machine learning model that integrates three deep neural network models: MobileNet, Inception, and ResNet. The choice of these models is motivated by their proven effectiveness in image classification tasks, their ability to handle large datasets, and their robustness to variations in disease presentation. By leveraging transfer learning, these pre-trained models are fine-tuned on our extensive dataset of diseased and healthy plant leaves, allowing them to capture intricate patterns and features specific to each disease. The ensemble approach strategically combines the strengths of individual models, enhancing the precision and robustness of disease detection. This methodology represents a significant advancement in the field of plant disease detection, providing valuable support to farmers and agricultural experts by enabling early disease identification and intervention.

A. Proposed Algorithm

Step 1: First load the acquired data using the `imread()` method present in CV2:

Step 2: Segment the data into training and testing Sets: from `tensorflow.keras.preprocessing.image import ImageDataGenerator`

```
train_datagen = ImageDataGenerator  
(rescale=1/255, shear_range=0.2, zoom_range=0.2,  
horizontal_flip=True, validation_split=0.1)
```

Step 3: Normalize the data to remove anomalies

Step 4: Perform data augmentation to make the model robust:

To perform edge detection: `cv2.Canny(img, 100, 200)`

To flip the image: `cv2.flip(img, 0)`

To blur the image: `cv2.blur(img, (20, 20))`

For convolution `kernel = np.ones((7, 7), np.float32)`

`conv = cv2.filter2D(img, -1, kernel)`

Step 5: Implement Transfer learning, with models like MobileNet, Inception, ResNet

```
feature_extractor_model="https://tfhub.dev/google/imagenet/inception_v3/classification/5"pretrained_model_without_top_layer=hub.KerasLayer(feature_extractor_model, input_shape=(224, 224, 3), trainable=False)
```

similarly, used mobile net and ResNet models

Step 6: During this process evaluate all the models separately, using a confusion matrix, and compared their results using the respective recall, precision, and f1-scores.

Step 7: Combine the power of all the transfer learning models by using the ensemble learning technique used a deep stack library to combine the above models. Next, two classifiers, namely Random Forest Classifier and Extra Trees

Classifier, are specified as estimators for the second-level meta-learner. The meta-learner is the model responsible for amalgamating the predictions generated by the base models. It accepts the outputs or predictions from these base models as inputs and adapts its learning based on them how to best combine them to produce an improved prediction or decision and this is done using random forest.

Step 8: The evaluation measures to proposed model to compare it with the above models.

B. Data Collection

The foundation of the suggested plant disease detection model primarily relied on a dataset containing ten distinct classes. This dataset was derived from both Plant Village and a primary source. To facilitate for both the training and testing phases of the proposed model, a dataset was divided, allocating 80% for training and 20% for testing.

A thorough depiction of the dataset employed in this study is available in Table I.

TABLE I. DETAILS OF DATA SET USED FOR PROPOSED MODEL TRAIN AND TEST PURPOSE

S. No.	Crop Name	Disease	Test Image Data Set	Train Image Data Set
1	Pepper bell	Pepper bell Bacterial Spot	201	697
2	Pepper bell	Pepper bell Healthy	297	1034
3	Potato	Potato Late Blight	60	300
4	Potato	Potato Healthy	31	106
5	Potato	Potato Early Blight	60	300
6	Tomato	Tomato Spider Mites	336	1173
7	Tomato	Tomato Bacterial Spot	437	1488
8	Tomato	Tomato Leaf Mold	191	666
9	Tomato	Tomato Septoria Leaf Spot	355	1239
10	Tomato	Tomato Healthy	319	1113

C. Pre-Processing

Data preprocessing is a pivotal phase in machine learning that readies raw data for analysis and model training. It heightens the quality and dependability of machine learning models by eliminating noise, rectifying errors, and converting data into a format that aligns with the model's requirements. In the context of colored images, data preprocessing is even more important due to the complex nature of image data.

- Noise removal: Colored images frequently exhibit noise, which can pose challenges for machine learning models in extracting features and achieving precise predictions. Data preprocessing techniques such as Gaussian blurring and median filtering can be used to remove noise from images, improving the performance of machine learning models.

- Color space conversion involves representing colored images in various color spaces, such as RGB, HSV, and YCbCr. Different color spaces have different properties, and some color spaces may be better suited for a particular machine-learning task than others. Data preprocessing techniques can be used to convert images from one color space to another, making it easier for machine learning models to learn from the data.
- Image resizing: Machine learning models often require images to be a certain size. Data preprocessing techniques can be used to resize images to the correct size, improving the performance of the model.

D. Data Normalization

Effective data normalization is a pivotal step in data preprocessing, significantly improving the accuracy of models for crops image disease detection. This involves both scaling and standardizing the input data. For three-channel (RGB) images, as depicted in Fig. 2, the usual procedure entails calculating mean values for the RGB (Red, Green, and Blue) channels across the entire image dataset, often utilizing list comprehension. Notably, the red channel values demonstrate concentration towards lower values and a slight positive skew. Conversely, the green channel values appear more evenly distributed, featuring a prominent peak around 135, indicating a higher prevalence of green in these images. Lastly, the blue channel values exhibit the highest level of uniformity with minimal skew, but they display notable variation among images.

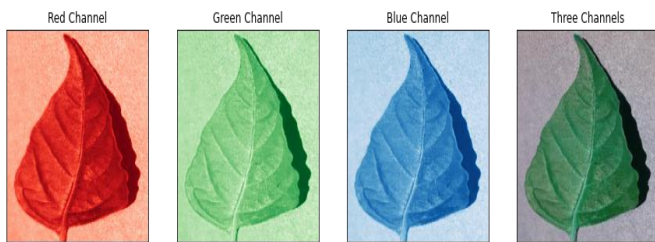


Fig. 2. RGB (Red, Green, and Blue) channels of leaves image.

E. Image Processing

1) *First, resize all the images to 224x224 pixels:* Using `cv2.resize()` and creating numpy arrays, these numpy arrays can be employed for exploratory data analysis. When working with three-channel (red, blue, green) images in a dataset, data normalization becomes a crucial step in data pre-processing. To avoid potential issues with unnormalized data, normalization should be performed for each channel separately as depicted in Fig. 3. This approach reduces the impact of outliers or extreme values in the data, thereby enhancing the overall model performance.

2) *Canny Edge Detection as shown in Fig. 4* is a prominent tool in image pre-processing that helps define the boundary of objects in an image. This efficient technique reduces noise in an image by allowing us to focus on the objects inside the specified boundary [16].

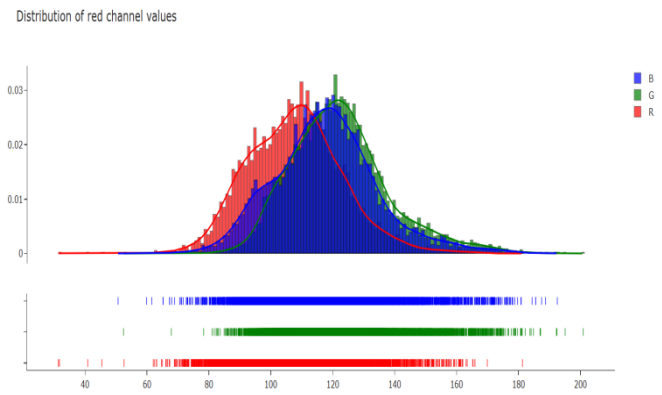


Fig. 3. RGB (Red, Green and Blue) distribution channel value.

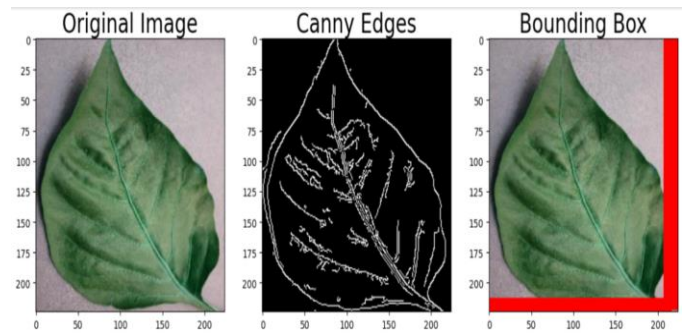


Fig. 4. Canny edge detection image.

3) *Further transformations are applied, such as flipping* as shown in Fig. 5, which involves reversing the rows and columns to achieve horizontal and vertical flipping. [16].

$$\text{Image} = A_{ijk}$$

$$\text{Horizontal flip: } A_{ijk} \rightarrow A_{i(n+1-j)k}$$

$$\text{Vertical flip: } A_{ijk} \rightarrow A_{(m+1-i)jk}$$

Although flipping maintains the same structure and features, a more diverse dataset can be created using this augmentation.

4) *Convolution is another augmentation technique* that performs a basic mathematical operation, in this a 2-D matrix window(kernel) moves across the length and breadth of the images shown in Fig. 6. It can be called a sunshine effect; this helps in building a robust and accurate model.

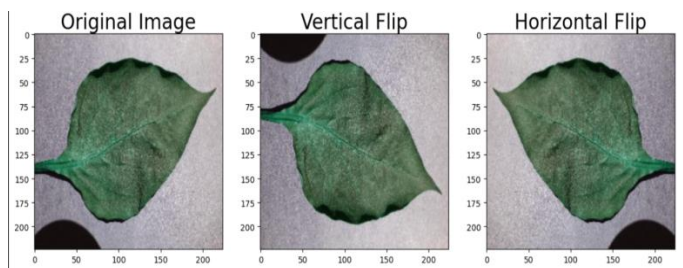


Fig. 5. Flip image.

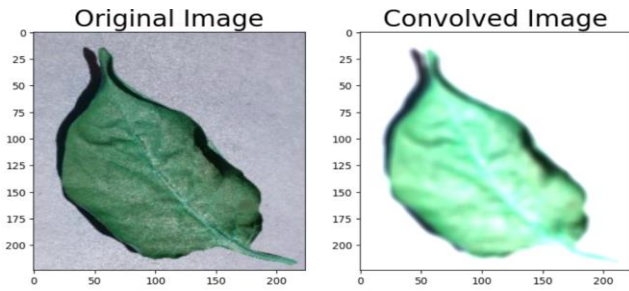


Fig. 6. Convolved image.

F. Proposed Ensemble Model

To create a deep ensemble model using the Dirichlet Ensemble class from the deep stack library, the process begins with the importation of the Keras Member class from deep stack library's base module. This class is instrumental in creating ensemble members from Keras models. Subsequently, three members are generated for the ensemble, with each one aligned to a fine-tuned pre-trained model. Each member is equipped with its corresponding pre-trained model, and data generators are customized for both the training and validation datasets. This methodology simplifies the generation of ensemble members trained on identical data, sharing a common architecture while having distinct initial weights. Following the successful creation of these ensemble members, the Dirichlet Ensemble class is then employed to establish and train the ensemble model using the train() method.

To accomplish this task, the necessary modules for constructing a stacked ensemble model are imported. These include the StackEnsemble class from the deep stack library and the ensemble module from scikit-learn, which houses the base learners and the stacking classifier.

Specifically, import the following:

- sklearn: The scikit-learn module.
- StackEnsemble: The StackEnsemble class from the deep stack library for creating the stacked ensemble model.

- RandomForestClassifier: A base estimator from the sci-kit-learn ensemble module.
- ExtraTreesClassifier: Another base estimator from the sci-kit-learn ensemble module.
- StackingClassifier: A meta-estimator from the sci-kit-learn ensemble module for stacking the base learners.
- LogisticRegression: A logistic regression classifier for the meta-learner in the stacking classifier.

The mentioned modules and classes can be employed to construct a stacked ensemble model, which consolidates predictions from multiple base learners through a meta-learner. The base estimators encompass a diverse range of machine learning algorithms, including decision trees, support vector machines, and neural networks. In the realm of deep stacking, the base learners frequently consist of deep neural networks trained on the same dataset with varied architectures or hyper parameters.

As illustrated in Fig. 7, the meta-learner serves as a dedicated machine learning algorithm, aiming to learn the optimal combination of predictions from base learners to enhance overall model performance. In the context of deep stacking, the meta-learner often takes the form of a simple linear model, such as logistic regression or a neural network. This meta-learner is fed with predictions from the base learners as input and gains the ability to assign weights, ultimately producing the final prediction.

In the final stage of our ensemble model, a weighted average approach is employed. This approach assigns different weights to the predictions made by each base learner in the ensemble. The weights are determined by the meta-learner based on the performance of each base learner during training. This means that predictions from more accurate base learners are given more importance in the final prediction. The use of a weighted average ensures that our ensemble model leverages the strengths of each individual model, leading to a more robust and accurate prediction.

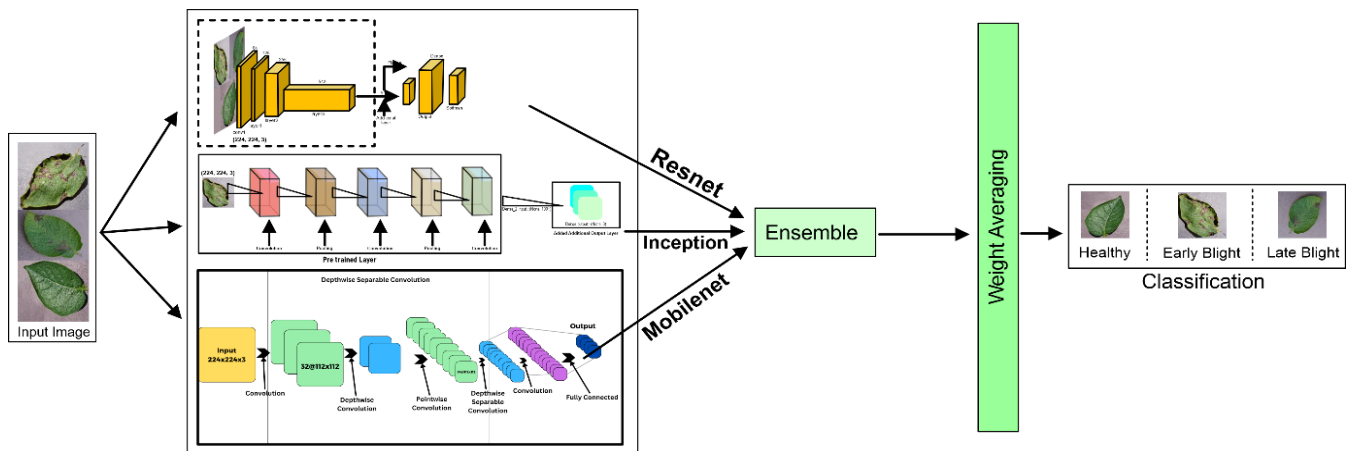


Fig. 7. Proposed model layer weighting average.

G. Proposed Model Training

All the member models are being compiled using the compile() function takes several arguments:

- **Optimizer:** specifies the optimizer algorithm used during training.
- **Loss:** designates the loss function employed during training, which quantifies the disparity between predicted and actual outcomes.
- **Metrics:** specifies the evaluation metric(s) that will be used to measure the model's performance during training.

All the member models are being fitted using the fit() function:

- **Train generator** refers to the input data generator responsible for producing batches of training data
- The **batch size** defines the quantity of samples utilized per gradient update throughout training, which has been set to 32.
- **Validation data** is the input data generator that generates batches of validation data.
- **Validation steps** specify the number of validation steps to evaluate the model after each epoch, which is 2
- **Verbose** is a flag that controls the level of logging during training. A value of 1 means that progress will be displayed during training.
- The model is trained using 10 epochs.

IV. RESULTS AND DISCUSSIONS

A. Model Training and Evaluation

To access the efficacy of the proposed disease detection model in comparison to established counterparts, an evaluation was undertaken on a comprehensive dataset featuring images of diseased plants. This dataset encompassed ten distinct diseases across three plant species: potato, tomato, and bell pepper. The consistent outcomes of these experiments underscore the superior performance of the suggested model in disease detection accuracy when contrasted with other existing models. In direct comparison to individual transfer learning models, the ensemble approach coupled with deep stacking techniques exhibited remarkable performance, achieving higher precision, recall, and F1 scores. This heightened accuracy can be attributed to the synergistic effect of ensemble learning and deep stacking, enabling the model to capture and leverage diverse patterns and features associated with diseases in the targeted plants. Moreover, the proposed model showcased enhanced robustness, resulting in a diminished risk of misclassification and false positives when compared to other models. The effectiveness of the proposed model in early disease identification underscores its potential for real-world applications in supporting farmers and agricultural experts. By facilitating timely interventions and early-stage disease management, the proposed model has the capacity to contribute

significantly to improved crop yields, minimized losses, and enhanced food security.

1) **MobileNet:** Based on Fig. 8, which illustrates Accuracy vs Epoch, it can be inferred that the model performs admirably shortly after 10 epochs. Notably, the accuracy of both Training and Validation sets exhibits minimal disparity, indicating robust model performance. The peak training accuracy stands at 97.4%, while the validation accuracy reaches 96.4%.

Fig. 9 provides insight into loss vs epochs. In this graph, both the training and validation losses undergo a sharp decrease after 10 epochs. The minimum loss values are achieved, with Training at 7.0% and Validation at 9.0%.

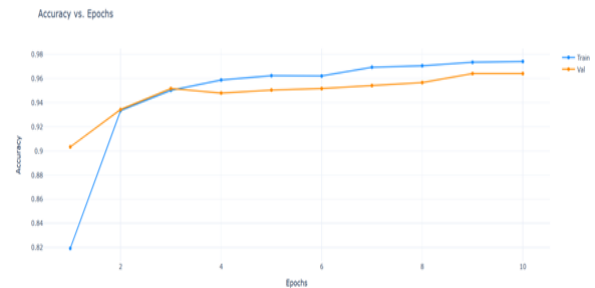


Fig. 8. Accuracy graph of mobilenet model.

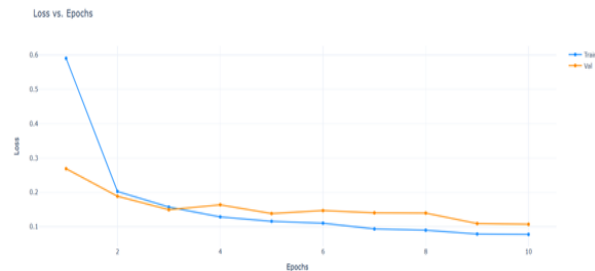


Fig. 9. Loss vs. Epochs mobilenet.

2) **Inception:** The accuracy vs epochs graph in Fig. 10 the peak training accuracy: 91.03% and validation:90.2% accuracy, with a high jump in accuracy just after 10 epochs loss vs epochs which are shown in Fig. 11 the rapid fall in the losses of training and validation data and with the having losses of 25% and 28% for training and validation respectively.

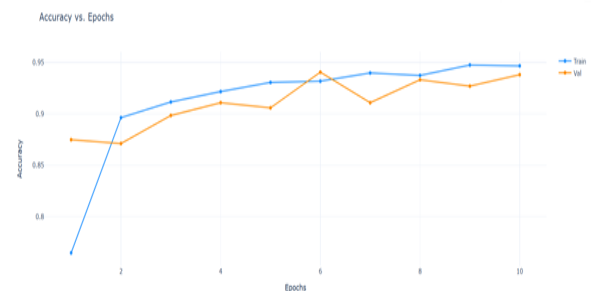


Fig. 10. Accuracy graph of inception model.

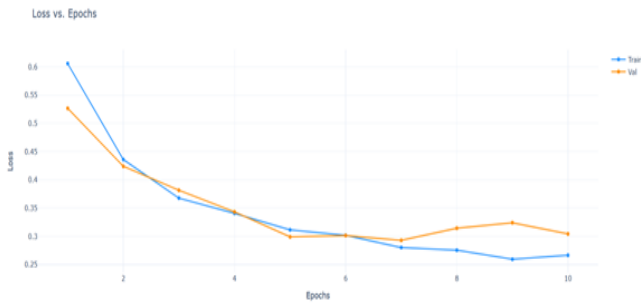


Fig. 11. Loss vs. Epochs of inception model.

3) *ResNet*: In Fig. 12, the accuracy vs. epochs plot reveals that within the first 2 epochs, there is a substantial increase in accuracy, ultimately reaching 94.66% for training and 94.05% for validation by the 10th epoch.

Fig. 13 displays the losses vs. epochs plot, where it is evident that low losses are achieved after 10 epochs for both Training and Validation. Specifically, Training records a 15.2% loss, while Validation exhibits a 15.3% loss after 10 epochs.

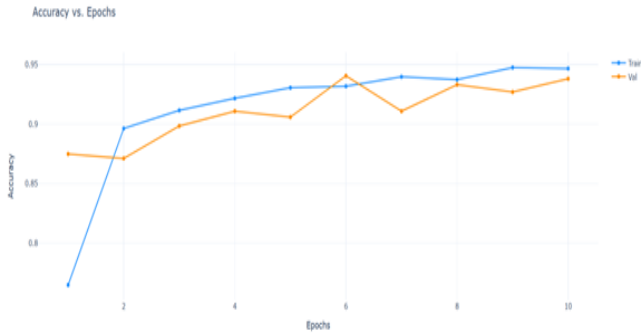


Fig. 12. Accuracy graph of resnet model.

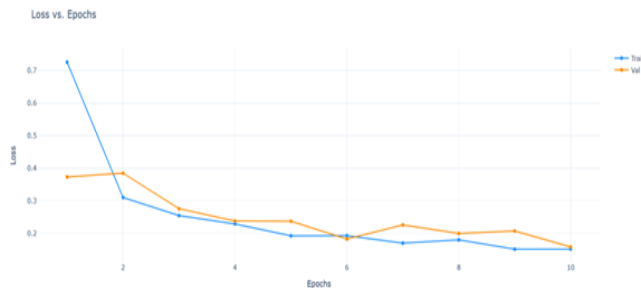


Fig. 13. Resnet Loss vs. Epoch graph of resnet model.

4) *Proposed model*: In Fig. 14, the accuracy vs. epochs plot illustrates that after 10 epochs, there is a significant increase in accuracy. By the 10th epoch, the accuracy reaches 94.66% for training and 94.05% for validation.

Fig. 15 depicts the plot of losses vs. epochs. As observed, low losses are achieved after 10 epochs for both Training and Validation. Specifically, Training records a 15.2% loss, while Validation exhibits a 15.3% loss after 10 epochs.

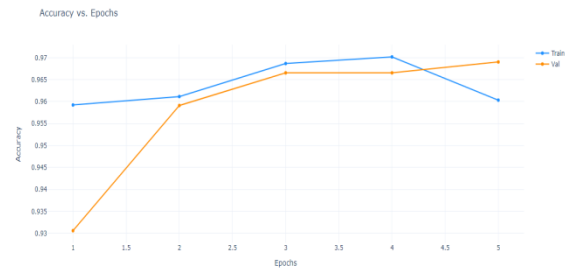


Fig. 14. Accuracy graph of proposed model.

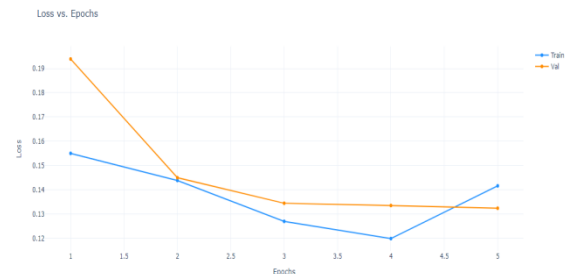


Fig. 15. Loss vs. Epoch graph of proposed model.

B. Performance Analysis

The experiments were carried out using the Keras framework and Tensor Flow-GPU on Google Colab. To gauge the effectiveness of the proposed methodology, various metrics, including accuracy, precision, F-score, recall, and loss, were employed.

Accuracy, encompassing both positive and negative classes, was computed to provide insights into the model's proficiency in categorizing images accurately. Precision, recall, and F-score were utilized to offer additional insights into the model's capacity to accurately predict both positive and negative classes.

1) *CNN confusion matrix*: In Fig. 16 the confusion matrix there are few classes which have been mispredicted significantly, such as Tomato Spider mites has been predicted Tomato healthy 58 times, therefore impacting the accuracy and precision also there is some mispredictions between the species since pepper bell bacterial spot has been predicted as Tomato Spider mites 16 times and rest there were some misclassifications between the tomato species. The weighted average f1 score was 0.9.

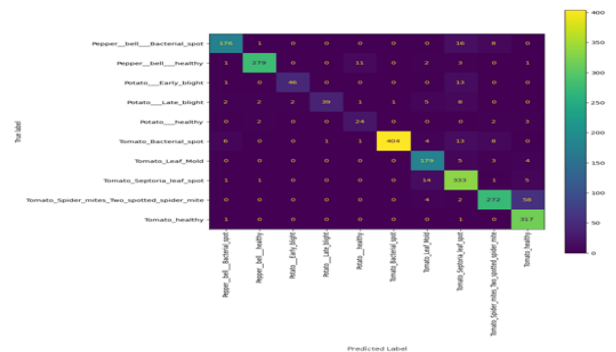


Fig. 16. Confusion matrix representation of the CNN model.

2) *Confusion Matrix MobileNet*: In Fig. 17 the confusion matrix there are a few classes that have been miss predicted slightly, such as Tomato Septoria Leaf has been predicted Tomato Bacterial Spot 17 times, and pepper bell healthy has been predicted as pepper bell bacterial spot 12 times and rest of misclassifications were less than four times. Therefore, the mispredictions were significantly less than the CNN model indicating higher accuracy and hence its weighted average f1 score was 0.96.

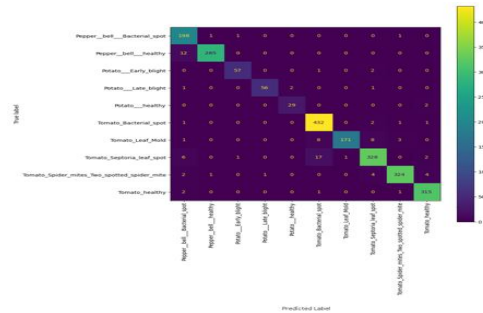


Fig. 17. Confusion matrix representation of the mobilenet model.

3) *Confusion matrix inception model*: Inception Models in Fig. 18 the confusion matrix some high misclassifications in Tomato Septoria and Tomato Spider mite classes with misclassifications ranging from 3-54 times. And from the above model's confusion matrix it can be inferred that these two classes are most difficult to predict. The inception model has been predicting other classes accurately like the mobile net model but these two classes namely Tomato Septoria and Tomato Spider mite where mispredicted significantly thereby impacting the models weighted average f1 score which comes out to be 0.9.

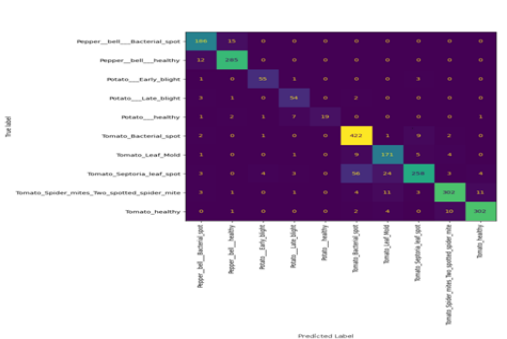


Fig. 18. Confusion matrix representation of the inception model.

4) *Confusion matrix resnet model*: In Fig. 19 confusion matrix shows some high misclassifications in Tomato Bacterial Spot and Tomato Leaf mold classes, which is different from the above models as they have been misclassifying some other classes and have been classifying these classes correctly. But the rest of the classes are correctly predicted and the mispredictions are less than equal to four times. Therefore, the weighted F1 score is 0.94 of the inception models.

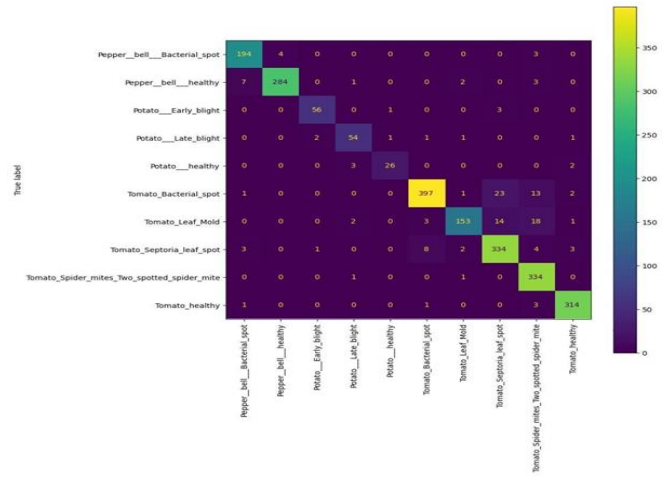


Fig. 19. Confusion matrix representation of the resnet model.

5) *Confusion matrix proposed ensemble model*: In Fig. 20 the proposed ensemble Model's confusion matrix showed much fewer misclassification than any of the above models. Only two classes Tomato Bacterial spot and Tomato Leaf Mold were wrongly predicted into some other tomato diseased classes and that too only 15 and 12 times respectively, However, apart from these instances, the majority of mispredictions were limited to two or fewer, underscoring the proposed model's superior performance in comparison to the aforementioned models across nearly all classes. The weight average F1 score, precision and recall are 0.97 greater than all the above models, showing its state-of-the-art performance.

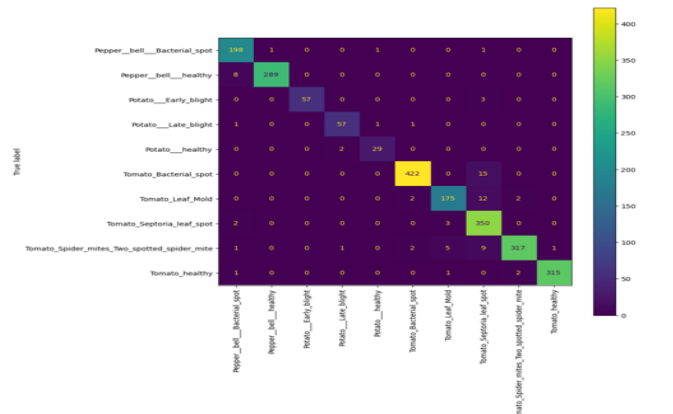


Fig. 20. Confusion matrix representation of the proposed ensemble model.

C. Comparative Analysis of Various Machine Learning Models with Proposed Model

Table II displays the outcomes derived from various models, each utilizing 10,403 images and undergoing 10 epochs for both training and validation. The results suggest that the Stack Ensemble model outperforms other models in terms of accuracy. Fig. 21. Show Comparative analysis of Obtained Results from the MobileNet, Inception, ResNet Models with Proposed Ensemble Model and Fig. 21 shows comparative analysis of proposed work with related Model.

TABLE II. OBTAINED RESULTS FROM THE DIFFERENT TECHNIQUES

Model	Images set	Classes of disease	Epoch	Validation Accuracy
CNN	10,403	10	10	90.05%
MobileNet	10,403	10	10	95.90%
Inception	10,403	10	10	89.91%
ResNet	10,403	10	10	93.80%
Stack Ensemble	10,403	10	10	97.86%
Dirichlet Ensemble	10,403	10	10	97.80%
Proposed Model	10,403	10	10	98.95%

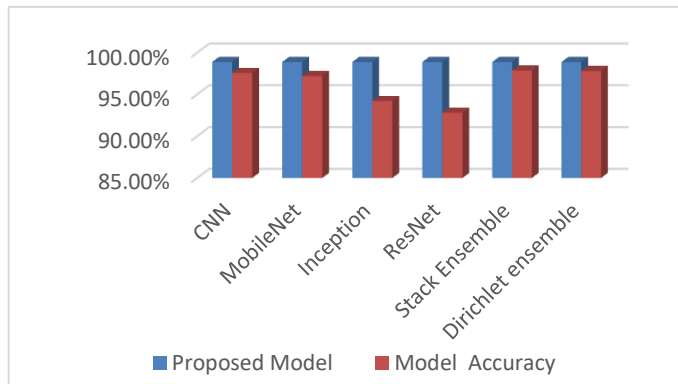


Fig. 21. Comparative analysis of obtained results from the different machine learning models with the proposed model.

V. CONCLUSION

The timely and precise detection and diagnosis of plant health issues play a pivotal role in ensuring global food production. This study offers a comprehensive evaluation of a plant health assessment system specifically designed for potato, tomato, and bell pepper plants. Through extensive experimentation and comparative analysis against existing models, the study emphasizes the exceptional performance of the proposed model in accurately identifying and categorizing plant health issues. The model has undergone training on a dataset containing 10,403 images. By adopting a combined approach that incorporates ensemble learning and deep stacking techniques, the model consistently outperforms individual transfer learning models. The model attains an outstanding accuracy rate of 98.95% in accurately identifying plant diseases. This notable enhancement can be credited to the synergistic collaboration of ensemble learning and deep stacking, enabling the model to discern and capitalize on diverse patterns and features linked to plant health issues in the specific crops. Additionally, the proposed model showcases improved reliability by reducing the risks of misclassification and false positives when compared to alternative models. This increased reliability holds particular significance in real-world applications, where the accurate and timely recognition of plant diseases is of paramount importance for farmers and agricultural specialists. The efficacy showcased by the proposed model in promptly identifying diseases underscores its potential to offer practical solutions for farmers. By enabling timely interventions and the management of diseases in their early stages, the model has the capacity to significantly enhance crop yields, mitigate losses, and contribute to overall

food security. This research underscores the substantial benefits of the proposed plant health assessment model and highlights its potential for real-world implementation. The integration of advanced techniques, improved accuracy, and enhanced reliability positions the model as a valuable tool in the field of agriculture, empowering farmers and experts to make well-informed decisions and effectively address plant health concerns.

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